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Chinese Journal of Aeronautics 23(2010) 430-437

Chinese Journal of Aeronautics

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Parametric Optimization Design of Aircraft Based on Hybrid Parallel Multi-objective Tabu Search Algorithm

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Received 22 October 2009; accepted 1 February 2010

Abstract

For dealing with the multi-objective optimization problems of parametric design for aircraft, a novel hybrid parallel multi-objective tabu search (HPMOTS) algorithm is used. First, a new multi-objective tabu search (MOTS) algorithm is proposed. Comparing with the traditional MOTS algorithm, this proposed algorithm adds some new methods such as the combination of MOTS algorithm and "Pareto solution", the strategy of "searching from many directions" and the reservation of good solutions. Second, this article also proposes the improved parallel multi-objective tabu search (PMOTS) algorithm. Finally, a new hybrid algorithm—HPMOTS algorithm which combines the PMOTS algorithm with the non-dominated sorting-based multi-objective genetic algorithm (NSGA) is presented. The computing results of these algorithms are compared with each other and it is shown that the optimal result can be obtained by the HPMOTS algorithm and the computing result of the PMOTS algorithm is better than that of MOTS algorithm.

Keywords: aircraft design; conceptual design; multi-objective optimization; tabu search; genetic algorithm; Pareto optimal

1. Introduction

Aircraft design is an iterative process of analyzing, integrating and decision making which is comprehensively utilizing the fruits of contemporary science and technology, systems engineering methodology and the engineering language to guide the manufacturing, testing and operating. Aircraft conceptual design belongs to the primary phase of aircraft development which lays the foundation for conducting detail design. The methods used in aircraft conceptual design include statistical method and systems design[1]. Aircraft conceptual design is performed on the basis of accurate and advanced engineering numerical methods as well as stable and efficient optimization algorithms, so the study and application of optimization algorithms become the key for the parametric design of aircraft.

Because aircraft conceptual design is always the issue of multi-objective optimization, all the objectives will not be able to reach optimums at the same time, so we must make tradeoff between these objectives[2]. Traditional multi-objective optimization algorithms often combine several objectives into a single objective by a set of weights, and then the solutions can be obtained by single-objective optimization. Due to the absence of the necessary priori knowledge to choose suitable weights and being sensitive to the shape of "Pareto front", the effectiveness of traditional multi-objective optimization algorithms is dissatisfactory. Until French economist V. Pareto[3] proposed the concept of "Pareto optimal", the optimal solution of multi-objective optimization was extended from a point to a set. The concept of "Pareto solution set" is a milestone for the study of multi-objective optimization. Since existing algorithms cannot achieve the perfect "Pareto solution set", we need to create some new method to solve multi-objective optimization effectively and obtain satisfactory noninferior set.

2. Multi-objective Tabu Search (MOTS) Algorithm

Tabu search algorithm is a heuristic algorithm with strong ability of local search[4]. In order to avoid falling into the local optima, the algorithm has two significant features: move operation and tabu list. The new candidate solution is generated by moving operations in the neighborhood of the current solution. To avoid cycling, the recently visited moves are classified as forbidden and stored in a tabu list so that every step of the algo-

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Foundation items: National Science Fund for Distinguished Young Scholars (10425208); Programme of Introducing Talents of Discipline to Universities (B07009)

doi: 10.1016/S1000-9361(09)60238-7

rithm is to choose the best move which is non-taboo. However, in some cases, if a tabu move improves upon the best solution found so far, then that move can be accepted. This is known as the aspiration criterion. Every complete cycle of tabu search algorithm is to determine the best candidate through selecting neighboring ones of the current solution, and then update the tabu list and designate the new candidate solution as the new current solution. The searching process continues like this until a predetermined stopping criterion is satisfied.

In fact, tabu search algorithm is used to solve the single-objective combinatorial optimization problem[5] and then is extended into the areas of multi-objective combinatorial optimization and multi-objective optimization within the continuous space. In the multi-objective optimization, the most important task is to find the Pareto optimal solution set. In addition, to determine the optimal neighbor is also critical. In the neighborhood of each current solution, the fitness function of the identified optimal solution is often defined as the weighted average of objectives. As the weight of every objective is being updated dynamically, the Pareto front of multi-objective optimization problems may be found out.

This article first provides a new tabu search algorithm, and then improves it and introduces another newer tabu search algorithm—hybrid tabu search algorithm combining the “Pareto front” -based multi-objective genetic algorithm with MOTS algorithm. The conclusions are then drawn through comparing the results of those algorithms.

2.1. A new MOTS algorithm

(1) Crucial steps and setting of parameters

1) Definition of fitness function

In this article, the fitness function of multi-objective optimization is prescribed as

$$\text{fitness} = \sum_{k=1}^{K} \lambda_k z_k$$

where z_k is the transformed individual objective function value of each $\boldsymbol{X} = [x_1 \quad x_2 \quad \cdots \quad x_m]$, λ_k the corresponding weight of each objective, and K the number of objectives.

To determine each objective z_k (adding the effect of restrictions), a fuzzy penalty function method[6] has been applied to transform the constrained multi-objective optimization problem into non-constrained one. The specific process is as follows:

Step 1 Normalizing the objective functions.

$$f_k' = \frac{1}{1+f_k}$$

where f_k is the individual objective function.

Step 2 Defining the penalty value which is used to evaluating the extent of constraint violation.

The resulting deviation of a point x_m from the jth constraint is

$$d_{mj} = \begin{cases} 0 & g_j(x_m) \le 0 \\ g_j(x_m) & \text{Otherwise} \end{cases}$$

Based on the fuzzy logic theory, the penalty values corresponding to different deviation ranges are

$$R_m = \begin{cases} 0 & 0 \le \max(d_{m1}, d_{m2}, \cdots, d_{mn}) \le 0.01 \\ 1 & 0.01 < \max(d_{m1}, d_{m2}, \cdots, d_{mn}) \le 0.05 \\ 2 & 0.05 < \max(d_{m1}, d_{m2}, \cdots, d_{mn}) \le 0.10 \\ 3 & 0.10 < \max(d_{m1}, d_{m2}, \cdots, d_{mn}) \le 0.20 \\ 4 & 0.20 < \max(d_{m1}, d_{m2}, \cdots, d_{mn}) \le 0.60 \\ 5 & 0.60 < \max(d_{m1}, d_{m2}, \cdots, d_{mn}) \le 1.00 \end{cases}$$

Step 3 Determining the transferred fitness function.

$$z_k = f_k' + R_m$$

The determination of fitness functions lies on the weight vectors of each of the objectives. Two measures are provided to determine weight vector[7-8]:

a) Each weight vector is set at $\boldsymbol{\lambda} = (\lambda_k, k = 1,2,\cdots,K)$ where $\lambda_k \in \{0, 1/r, \cdots, (r-1)/r, 1\}$ (r is determined by the decision makers) and $\lambda_k \ge 0$, and $\sum_{k=1}^{K} \lambda_k = 1$ should be satisfied.

b) For each objective k, nonnegative random weights λ_k ($\lambda_k \ge 0$) is set, then $\boldsymbol{\lambda} = [\lambda_1 \quad \lambda_2 \quad \cdots \quad \lambda_K]$ is normalized and put $\sum_{k=1}^{K} \lambda_k = 1$.

2) Generation of initial solution

The procedure of generating the initial solution of tabu search algorithm is as follows:

Step 1 Randomly generating an initial point within the specified range of each variable.

Step 2 If $R_m = 0$, turning to Step 3, otherwise turning to Step 1.

Step 3 Setting the current point as a initial feasible solution.

3) Selection of neighborhood solution

When the current value is set at $\boldsymbol{x}^0 = (x_i^0, i = 1,2,\cdots,M)$, the neighborhood solutions will be selected based on the following principle[9]:

$$x_i = x_i^0 + R(x_i^{\max} - x_i^{\min}) / 10^n$$

where R is a random number within the interval [–1, 1], x_i^0 is the current value of variable x_i, and the step length of variable is determined by the value of n which is depending on the calculation precision. In the process of exploring the neighborhood of the current point, some neighborhood solutions may be located outside the defined interval of independent variable, thus it is necessary to judge whether they are within the variable interval of the independent variable. If not, the solution will be deleted and a new neighborhood solution should be generated.

4) Combination of MOTS algorithm and "Pareto solution"

Comparing with traditional optimization algorithm, the tabu search algorithm applied to multi-objective optimization must be bound to involve the mutual coordination among these objectives. In order to solve this problem, we must obtain the non-dominated sotulion set of the problem. The concept of "Pareto solution" is introduced into tabu searching so as to strive for finding the "Pareto front" of the problem which is better than the best solution for one certain objective. The implementation process is as follows:

a) In every searching step for one certain weight vector, the neighborhood set of the current solution is always merged with the set of efficient solutions obtained in the former step, then the non-dominated solutions are sought from the union.

b) To obtain the general non-dominated solution set for one certain weight vector, the non-dominated solution sets of all searching steps are always merged together, and then the non-dominated solution sets are sought from the union.

c) To obtain the general non-dominated solution set for all weight vectors, the non-dominated solution sets corresponding to every weight vector are always merged together, then the non-dominated solutions are sought from the union.

For a certain weight vector, the whole process of MOTS algorithm is shown as Fig.1. If we are searching

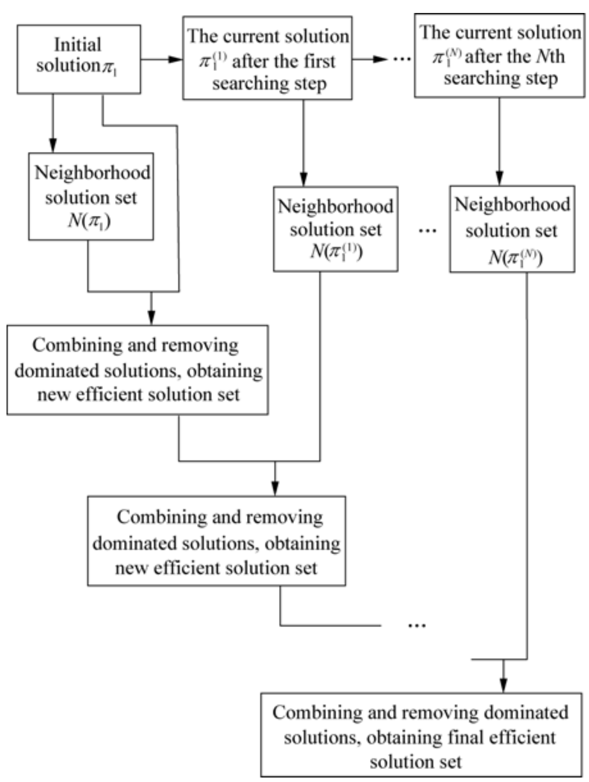

Fig.1 Module of MOTS algorithm.

from different "directions" (namely choosing different weight vectors) simultaneously, then we must run through this process separately for different weight vectors. Finally, we can combine all the results and obtain the non-dominated solution set of the sum aggregate.

5) The strategy of "searching from many directions"

In order to expand the searching area of tabu search and enhance the diversity of solutions, a new strategy of "searching from many directions" is adopted. We can set many "searching directions", namely many weight vectors. A normal tabu searching is carried out for every weight vector, and then we merge the non-dominated solution sets corresponding with all weight vectors as follows: $E = E_0 \cup E_1 \cup \cdots \cup E_s$, where E is the set of efficient solutions. Obviously, comparing with one single weight vector, the sum aggregate must include more non-dominated solution sets. The flowchart is shown as Fig.2.

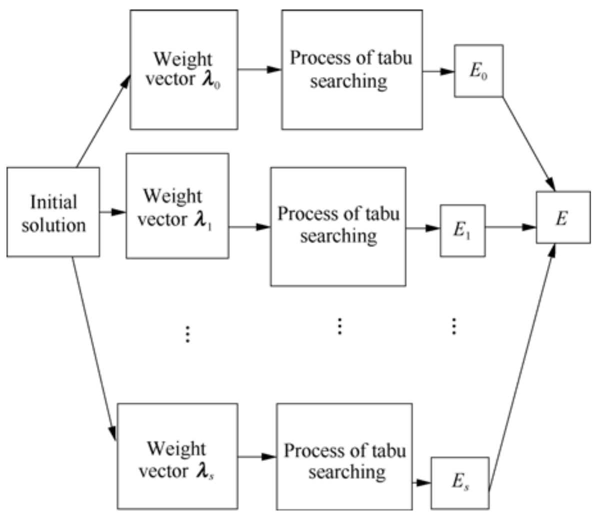

Fig.2 Process of "searching from different directions".

6) Reserving mechanism of good solutions

a) In every searching step for one certain weight vector $\boldsymbol{\lambda}_v$, the neighborhood set of the current solution is always merged with the optimal solution set to insure that the best solutions in the neighborhood set is being reserved.

b) For one certain weight vector $\boldsymbol{\lambda}_v$, the optimal solution sets of all searching steps are always merged together to insure the best solutions of the whole iterative process are not to be lost.

c) For all weight vectors $\boldsymbol{\lambda}_v$ ($v = 0,1,\cdots,s$), all the optimal solution sets corresponding to all weight vectors are always merged together to insure that the best solutions of the whole process are being included.

(2) Running steps of algorithm (two objectives)

Step 1 Initialization. Randomly generating an initial feasible solution π_i; defining the efficient solutions set $E=\Phi$ and the tabu list $T_L=\Phi$.

Step 2 Iterating.

1) $\pi^0=\pi_i$.

2) $E_v=\{\pi^0\}, \lambda_v=v/s$ (where $v=0,1,\cdots,s$, and s is a non-negative integer which is set in advance).

3) Cycling: a) randomly selecting N neighborhood solutions around π^0 (being not tabu moves and/or satisfying the aspiration criterion and establishing the neighborhood solution set $N(\pi^0)=\{\pi^u$: $u=1,2,\cdots,N\}$; b) setting $E_v=E_v\cup N(\pi^0)$, and removing all dominated solutions from E_v; c) for each π^u, separately calculating the value of individual objective $z_1(\pi^u)$ and $z_2(\pi^u)$; d) selecting π^{u^*} meeting the following conditions:

$$z_{\lambda_v}(\pi^{u^*})=\min_{u=1,2,\cdots,N}\left[\lambda_v z_1+(1-\lambda_v)z_2\right] \tag{1}$$

e) setting $\pi^0=\pi^{u^*}$, and updating T_L; f) If $N_{count}<N_{max}$ (where N_{count} is the current times of iteration, and N_{max} the given maximum times of iteration) setting $N_{count}=N_{count}+1$, and turning to step a), otherwise turning to the next step.

4) Setting $E=E\cup E_v$

(3) Removing all dominated solutions from E and outputting E.

2.2. *Parallel multi-objective tabu search (PMOTS) algorithm*

(1) Modification to the initial solution

Since the initial solution can greatly affect the result of the MOTS algorithm, the method of generating initial solution is crucial to this algorithm. The modification steps are then introduced:

Step 1 Iterating following steps for N_m times (N_m is a large natural number): 1) randomly selecting a initial point within the specified range of variables; 2) if R_m=0, turning to 3), otherwise turning to 1); 3) registering current point as a initial feasible solution.

Step 2 Putting those initial feasible solutions into the set $S=\{x_i: i=1,2,\cdots,N_m\}$, and removing dominated solutions form S.

Step 3 Regarding the set obtained in Step 2 as the initial solution set of the PMOTS algorithm.

(2) Modification to the structure of the algorithm

Traditional tabu search algorithms always start searching from one point and march by the way of "point to point" in the whole process. If we adopt parallel searching way to start searching from many initial points at the same time and then merge the solution sets corresponding to all paths, the number and diversity of solutions are greatly increased. The parallel searching can be executed with many computers simultaneously, or carried out with a single one which is called as "pseudo parallel". The structure of the PMOTS algorithm is shown as Fig.3.

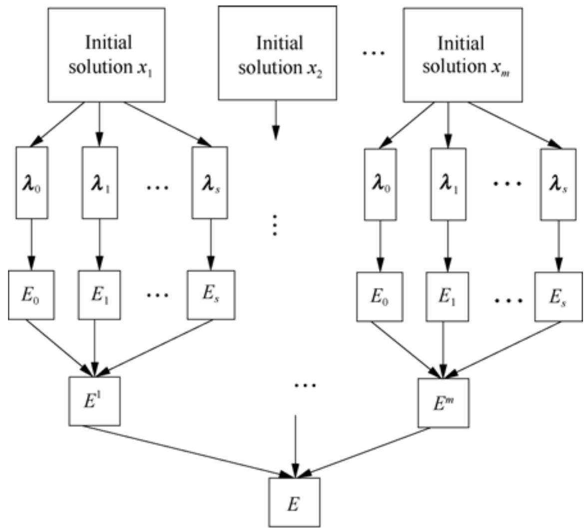

Fig.3 Structure of PMOTS algorithm.

3. Hybrid Parallel Multi-objective Tabu Search (HPMOTS) Algorithm

As the results of the MOTS algorithm are greatly affected by the initial values, it can be deduced that if a proper initial value is selected, then the Pareto solution may be obtained more easily from the searching results. Based on this idea, the generic algorithm is combined with tabu search algorithm. The genetic algorithm will be run first for limited times and then their results will be put into the feasible initial solution set S of tabu search algorithm so as to reduce the blindness of tabu search in striving to obtain the solution which is closer to "Pareto front" through tabu search algorithm.

3.1. *Way of combing PMOTS algorithm with NSGA*

Although the PMOTS algorithm provide a method to choose initial solutions, sometimes the quality of initial solutions cannot be guaranteed owing to the randomness of initial solution. We intend to utilize the merits of genetic algorithm having strongest global searching ability[10] and tabu search having the strongest local searching ability[3] to combine these two algorithms and create a new hybrid algorithm. The combining procedure is as follows:

(1) A new genetic algorithms—non-dominated sorting genetic algorithm NSGA[11] is applied to perform roughly computation. On the account of computing time, a relatively small number may be selected as the maximum evolutionary generations.

(2) The results of NSGA are put into the feasible initial solution set of the MOTS algorithm, then the local searching around every initial solution can be started.

3.2. *Basic steps*

(1) Initialization: each variable is randomly taking a value within the specified interval, and the randomly

selected certain number of individuals will make up the initial population.

(2) Evaluating each individual and using penalty function method to evaluate the degree of individual's satisfying the constraint conditions.

(3) Selecting the first class points of the population, and storing them into the non-dominated solution set *M*.

(4) Reproducing, crossing and mutating.

(5) Putting children into Pareto-set filter after the genetic operation.

(6) When the number of iterations exceeds the number of maximum evolutionary generation, terminating the operation of the algorithm.

(7) Outputting the non-dominated solution set *M*.

(8) Regarding the non-dominated solution set obtained in Step (7) as the feasible initial solution set.

(9) Cycling: for each x_i in the *S*, implement the algorithm in Section 2.1 (2) repeatedly.

(10) Obtaining the total non-dominated solution set: merging all *E* values which are corresponding to the x_i values obtained in Step (9) and then obtaining non-dominated solution sets of the sum aggregation.

4. Example and Results

4.1. Optimization of an airliner conceptual design

In the example of the bi-objective optimization design of arterial aircraft of Ref.[12], the wing area *A*, fuselage length *l*, wing span *b*, installed thrust T_i and take-off weight W_TO are selected as independent variables, and other factors are regarded as fixed parameters. The concept analysis is constituted of four modules: drag characteristics, aerodynamics, weight and performance. The known conditions, objectives and constraints are described as follows.

(1) Variables and boundaries:

$$\begin{cases} \text{Wing area (m}^2\text{)}: 111 \le A \le 232 \\ \text{Fuselage length (m)}: 32 \le l \le 45.7 \\ \text{Wing span (m)}: 26 \le b \le 42.7 \\ \text{Installed thrust (kg)}: 12\,587 \le T_\mathrm{i} \le 24\,948 \\ \text{Take-off weight (kg)}: 63\,504 \le W_\mathrm{TO} \le 113\,400 \end{cases}$$

(2) Constraint:

$$\begin{cases} \text{Take-off field length (m)}: S_\mathrm{T} \le 1\,981 \\ \text{Landing field length (m)}: S_\mathrm{L} \le 1\,372 \\ \text{Overall fuel balance coefficient}: R_\mathrm{f} \ge 1.0 \\ \text{Climb gradient, take-off (°)}: q_\mathrm{T} \ge 2.7 \\ \text{Missed approach climb gradient, landing (°)}: q_\mathrm{L} \ge 2.4 \\ \text{Payload fraction}: U \ge 0.3 \end{cases}$$

(3) Objectives:

$$\max C_L/C_D,\ U$$

where *U* is the effective load coefficient, and C_L/C_D the lift-drag ratio.

4.2. Comparison of running results of different algorithms

(1) The running result of the MOTS algorithm

Firstly, we apply the MOTS algorithm mentioned in Section 2.1 to the optimization design, and the basic parameters used in the algorithm is as follows: $s=100$; N=100; $N_{\max}$=50. The results of the random operation are shown in Table 1. The data of Row ※ are the initial points of this algorithm, and the following Rows 1-19 are final non-dominated solution sets. Fig.4 shows the distribution of these points.

Table 1 Running results of MOTS algorithm

Row	A/m^2	l/m	b/m	T_i/kg	W_TO/kg	q_L/(°)	q_T/(°)	S_L/m	S_T/m	R_f	C_L/C_D	U
※	212.4	45.7	38.68	24 647	113 023	7.58	2.67	1 177	1 396	1.09	17.39	0.461 00
1	204.1	43.9	42.67	17 087	95 461	6.57	2.70	1 038	1 472	1.00	19.81	0.498 94
2	185.1	45.4	42.62	18 366	95 892	7.21	3.14	1 141	1 526	1.00	19.96	0.494 98
3	184.8	45.7	42.58	18 299	95 869	7.17	3.11	1 142	1 534	1.00	19.94	0.495 21
4	188.9	45.5	42.64	18 167	95 881	7.11	3.06	1 119	1 512	1.00	19.92	0.495 69
5	207.2	42.5	42.66	17 565	95 818	6.79	2.82	1 028	1 426	1.00	19.82	0.497 67
6	211.6	43.2	42.65	17 202	95 790	6.60	2.70	1 007	1 423	1.00	19.74	0.498 95
7	169.8	45.6	42.66	20 189	96 736	8.08	3.79	1 249	1 548	1.00	20.15	0.489 55
8	173.4	45.7	42.67	19 965	96 713	7.97	3.70	1 224	1 532	1.00	20.11	0.490 30
9	178.4	45.5	42.60	19 784	96 780	7.86	3.61	1 774	2 240	1.00	20.03	0.491 00
10	178.5	45.5	42.59	19 780	96 789	7.86	3.60	1 192	1 505	1.00	20.02	0.491 05
11	183.9	44.6	42.60	19 698	96 827	7.81	3.56	1 160	1 470	1.00	20.00	0.491 37
12	185.4	44.1	42.56	19 633	96 801	7.78	3.54	1 151	2 175	1.00	19.98	0.491 50
13	192.9	42.0	42.56	19 595	96 818	7.76	3.52	1 111	1 412	1.00	19.96	0.491 70
14	192.0	36.0	42.66	18 610	98 593	6.91	2.96	1 141	1 534	1.03	20.16	0.483 43
15	187.3	34.7	42.66	18 604	98 600	6.89	2.95	1 168	1 571	1.04	20.22	0.482 35
16	182.1	36.2	42.67	18 600	98 627	6.88	2.96	1 200	1 614	1.04	20.28	0.481 48
17	168.8	35.7	42.62	18 564	98 621	6.82	2.94	1 288	1 737	1.05	20.42	0.479 04
18	157.1	34.7	42.66	18 582	98 641	6.80	2.96	2 054	2 767	1.06	20.58	0.476 61
19	227.1	43.6	42.67	17 468	96 759	6.66	2.70	953	1 338	1.00	19.57	0.498 99

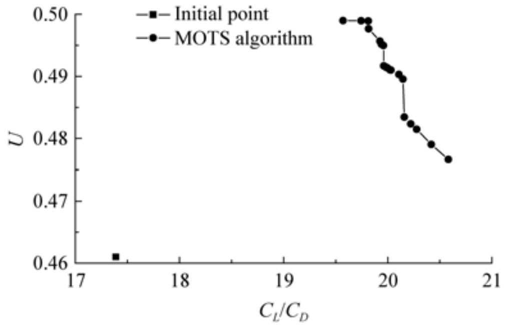

Fig.4 Running results of MOTS algorithm.

(2) The running results of the PMOTS algorithm

The running results of the PMOTS algorithm can be seen in Table 2 and Fig.5. The data of Rows ※1-※5 in Table 2 are initial solutions of the PMOTS algorithm, and the data of Rows 1-33 are final solution sets of the PMOTS algorithm. Compared with the running result of the MOTS algorithm, the running result of the PMOTS algorithm is excellent (see Fig.6).

(3) The running results of the HPMOTS algorithm

Applying the HPMOTS algorithm mentioned in Section 2.2 to the aircraft bi-objective optimization design, the basic parameters are as follows: population size =

Table 2 Running results of PMOTS algorithm

Row	A/m^2	l/m	b/m	T_i/kg	W_{TO}/kg	q_L/(°)	q_T/(°)	S_L/m	S_T/m	R_f	C_L/C_D	U
※1	231.7	45.6	39.25	22 852	103 638	8.29	3.27	992	1 175	1.00	18.01	0.488 05
※2	232.0	45.7	38.48	22 885	104 166	8.14	3.04	994	1 183	1.00	17.67	0.488 50
※3	232.0	45.6	41.37	20 137	104 132	6.99	2.70	1 003	1 323	1.04	18.93	0.481 84
※4	232.2	45.7	40.44	20 637	104 066	7.17	2.70	998	1 292	1.03	18.52	0.484 21
※5	232.2	45.7	37.97	22 404	104 180	7.82	2.73	992	1 204	1.00	17.44	0.489 76
1	207.6	44.2	42.64	17 177	95 721	6.59	2.70	1 024	1 449	1.00	19.75	0.498 97
2	206.3	44.7	42.65	17 195	95 733	6.60	2.70	1 030	1 457	1.00	19.76	0.498 93
3	228.9	43.4	42.67	17 481	96 835	6.65	2.70	1 409	1 329	1.00	19.56	0.498 99
4	166.9	44.2	42.66	16 546	93 534	6.45	2.70	1 226	1 776	1.00	20.21	0.498 58
5	153.0	38.3	42.66	19 131	95 968	7.51	3.47	1 373	1 765	1.01	20.56	0.485 12
6	149.3	41.9	42.67	17 765	94 146	7.00	3.11	1 374	1 866	1.00	20.49	0.492 15
7	148.4	40.8	42.66	17 750	94 150	7.00	3.11	1 382	1 876	1.00	20.53	0.491 40
8	149.9	42.1	42.66	17 760	94 125	7.02	3.12	1 368	1 857	1.00	20.47	0.492 36
9	149.6	40.2	42.66	17 751	94 150	7.00	3.12	1 372	1 862	1.00	20.54	0.491 28
10	152.5	43.3	42.64	17 749	94 154	7.02	3.11	1 345	1 829	1.00	20.39	0.493 56
11	149.0	43.0	42.66	17 793	94 152	7.04	3.13	1 375	1 865	1.00	20.45	0.492 73
12	150.2	42.2	42.66	17 787	94 143	7.04	3.13	1 365	1 851	1.00	20.46	0.492 54
13	151.0	42.4	42.64	17 783	94 143	7.03	3.12	1 358	1 842	1.00	20.44	0.492 81
14	149.0	42.4	42.65	17 784	94 147	7.03	3.12	1 375	1 866	1.00	20.46	0.492 42
15	149.3	41.6	42.67	17 795	94 153	7.03	3.13	1 374	1 861	1.00	20.50	0.491 96
16	149.7	41.8	42.65	17 800	94 148	7.04	3.13	1 370	1 856	1.00	20.48	0.492 19
17	160.0	41.8	42.67	17 705	94 170	7.00	3.09	1 287	1 752	1.00	20.37	0.493 90
18	156.9	40.8	42.67	17 735	94 167	7.01	3.10	1 312	1 781	1.00	20.43	0.492 80
19	155.6	41.2	42.66	17 730	94 162	7.00	3.10	1 322	1 796	1.00	20.44	0.492 79
20	155.1	42.4	42.67	17 750	94 153	7.02	3.11	1 324	1 799	1.00	20.41	0.493 42
21	156.2	42.4	42.65	17 734	94 150	7.02	3.10	1 316	1 789	1.00	20.39	0.493 62
22	150.7	41.5	42.65	17 741	94 146	7.00	3.11	1 361	1 849	1.00	20.48	0.492 22
23	153.0	39.7	42.67	17 732	94 157	6.99	3.11	1 344	1 825	1.00	20.52	0.491 55
24	151.1	42.1	42.65	17 728	94 156	7.00	3.10	1 358	1 847	1.00	20.45	0.492 60
25	150.4	42.3	42.67	17 740	94 145	7.01	3.11	1 364	1 853	1.00	20.46	0.492 57
26	166.0	42.2	42.66	17 616	94 158	6.97	3.05	1 243	1 699	1.00	20.28	0.495 20
27	157.8	44.7	42.65	17 448	94 165	6.87	2.98	1 301	1 798	1.00	20.29	0.495 19
28	158.5	45.2	42.65	17 456	94 164	6.88	2.98	1 295	1 789	1.00	20.26	0.495 66
29	158.1	44.4	42.67	17 448	94 166	6.87	2.98	1 299	1 794	1.00	20.30	0.495 08
30	162.1	44.5	42.66	17 464	94 165	6.89	2.98	1 269	1 752	1.00	20.25	0.495 85
31	161.8	42.7	42.65	17 472	94 155	6.88	2.99	1 273	1 754	1.00	20.31	0.494 87
32	159.7	43.9	42.65	17 471	94 158	6.88	2.99	1 287	1 776	1.00	20.29	0.495 10
33	161.7	45.3	42.67	17 476	94 156	6.90	2.99	1 271	1 754	1.00	20.23	0.496 30

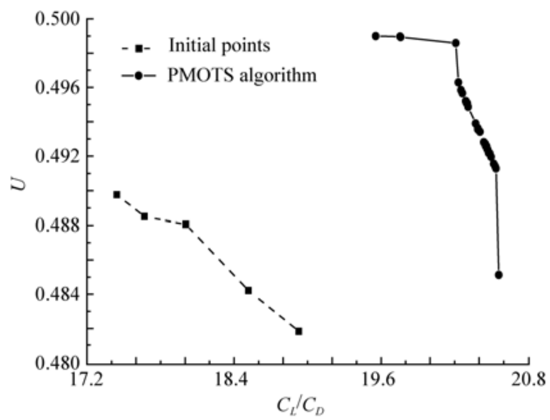

Fig.5 Running results of PMOTS algorithm.

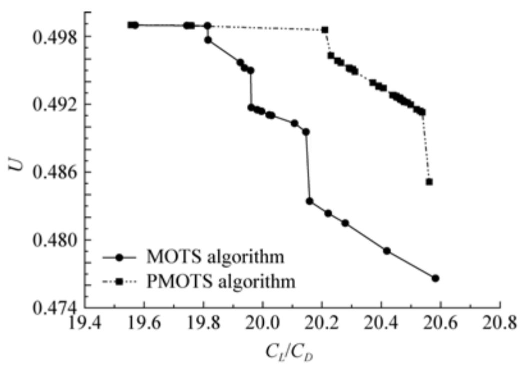

Fig.6 Comparison of running results between MOTS and PMOTS algorithms.

500; maximum generation = 50; crossover probability = 0.85; mutation probability = 0.05; s=100; N= 100 and $N_{\max}$ = 50, the corresponding results are shown in Table 3 and Fig.7. The data of Rows ※1-※4 are the results after running genetic algorithms (as initial solution set) of the HPMOTS algorithm, and the data of Rows 1-16 are the final non-dominated solution sets.

Table 3 Running results of HPMOTS algorithm

Row	A/m^2	l/m	b/m	T_i/kg	W_{TO}/kg	q_L/(°)	q_T/(°)	S_L/m	S_T/m	R_f	C_L/C_D	U
※1	229.3	45.4	40.16	20 479	100 968	7.52	2.91	978	1 246	1.00	18.42	0.493 07
※2	219.3	44.1	42.66	19 075	97 799	7.40	3.20	995	1 305	1.00	19.64	0.494 51
※3	186.4	38.4	42.66	17 371	96 469	6.52	2.70	1 146	1 611	1.02	20.17	0.489 69
※4	163.7	37.1	42.61	22 620	97 780	9.18	4.62	1 314	1 477	1.00	20.45	0.481 05
1	227.5	44.7	42.66	17 519	96 959	6.66	2.70	953	1 337	1.00	19.53	0.499 03
2	156.0	44.8	42.65	16 650	93 192	6.54	2.76	1 300	1 860	1.00	20.30	0.498 25
3	155.9	45.3	42.62	16 575	93 132	6.50	2.72	1 301	1 868	1.00	20.27	0.498 54
4	167.6	42.4	42.65	16 462	93 180	6.44	2.70	1 218	1 754	1.00	20.25	0.498 89
5	231.1	45.2	42.67	17 594	97 248	6.68	2.70	9 42	1 320	1.00	19.48	0.499 06
6	168.8	45.2	42.67	16 582	93 686	6.46	2.70	1 214	1 748	1.00	20.16	0.499 01
7	155.2	40.5	42.67	16 724	93 556	6.50	2.76	1 317	1 875	1.00	20.46	0.494 35
8	151.3	37.7	42.66	16 741	93 578	6.48	2.76	1 351	1 920	1.01	20.58	0.492 28
9	147.9	37.1	42.65	16 737	93 587	6.47	2.76	1 381	1 963	1.01	20.63	0.491 46
10	148.1	36.8	42.66	16 770	93 569	6.49	2.78	1 379	1 956	1.01	20.64	0.491 44
11	147.9	34.4	42.67	16 799	93 573	6.50	2.79	1 382	1 955	1.01	20.66	0.490 91
12	171.2	37.9	42.65	17 440	93 617	6.93	3.03	1 203	1 647	1.00	20.34	0.495 89
13	170.2	38.9	42.63	17 361	93 620	6.88	3.00	1 209	1 663	1.00	20.32	0.496 17
14	178.2	41.7	42.66	16 573	93 615	6.46	2.67	1 156	1 660	1.00	20.16	0.498 96
15	196.3	45.2	42.67	17 018	95 212	6.56	2.67	1 072	1 526	1.00	19.86	0.499 03
16	229.4	45.5	42.66	17 586	97 210	6.68	2.67	948	1 329	1.00	19.49	0.499 05

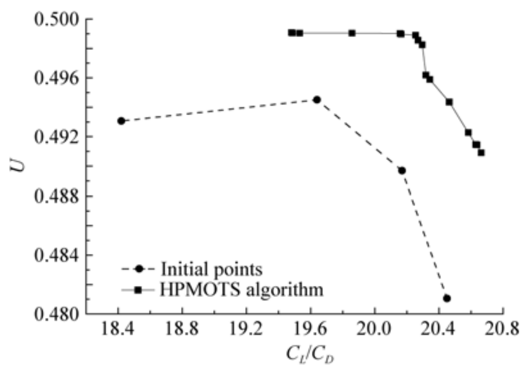

Fig.7 Running results of HPMOTS algorithm.

(4) The comparison of different MOTS algorithms

If we put the results obtained from different MOTS algorithms in one figure and make comparison (See Fig.8), final conclusion is easy to be drawn: the HPMOTS algorithm is winner.

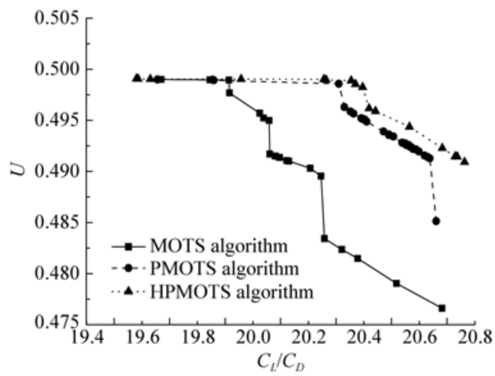

Fig.8 Comparison of running results by three MOTS algorithms.

5. Conclusions

(1) Comparing with the simple tabu search algorithm, the PMOTS algorithm with stronger global optimization ability is more effective than the MOTS algorithm, and its solutions can dominate the non-dominated solution sets of the latter.

(2) The HPMOTS algorithm combing the MOTS algorithm with NSGA is the best and can completely dominate the results obtained by the former two algorithms.

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